

## **REMARKS**

### **I. INTRODUCTION**

Claims 1 and 15 have been amended. No new matter has been added. Thus, claims 1-15 remain pending in the present application. In view of the following remarks, it is respectfully submitted that all of the presently pending claims are allowable.

### **II. THE 35 U.S.C. § 103(a) REJECTIONS SHOULD BE WITHDRAWN**

Claims 1-15 stand rejected under 35 U.S.C. § 103 as per discussion in the previous non-final office action, which the Examiner incorporates by reference. (See 1/21/09 Office Action, p. 2-3).

Claims 1, 2, and 15 stand rejected under 35 U.S.C. § 103(a) as being unpatentable over “General Object Reconstruction Based on Simplex Meshes” by Delingette, published in the International Journal of Computer Vision, vol. 32, pp. 111-142, 1999 (hereinafter “Delingette”). (See 7/11/08 Office Action, p. 12-14). Claims 3-7 stand rejected under 35 U.S.C. § 103(a) as being anticipated by Delingette in view of U.S. Patent No. 6,968,299 to Bernardini et al. (hereinafter “Bernardini”). (See 7/11/08 Office Action, p. 15-18). Claims 8-14 stand rejected under 35 U.S.C. § 103(a) as being anticipated by Delingette in view of Bernardini and in further view of U.S. Patent No. 6,201,889 to Vannah (hereinafter “Vannah”). (See 7/11/08 Office Action, p. 18-23).

Delingette describes a general tridimensional reconstruction algorithm of volumetric images, based on deformable simplex meshes. (See Delingette, Abstract). In this paper, the author describes a refinement algorithm based on the minimization of a geometric criterion based on the distance to the data or the local curvature. (See Delingette, p. 115, col. 1, para. 3). The simplex meshes are unstructured meshes, and can therefore be locally refined or decimated. (See Delingette, p. 118, col. 2, para. 3). In this passage cited by the Examiner (See 7/11/08 Office

Action, p. 12-13), there is no suggestion of setting a higher resolution when reliable image features are found and setting lower resolution in the opposite case. In fact, Delingette increases its resolution in areas of high curvature. (See Delingette, p. 121, figure 9b). Delingette's refinement measure is linked to the maximum distance to the data. (See Delingette, p. 133, col. 2, para. 5). Also, Delingette states that its algorithm is not sensitive to noise. (See Delingette, p. 127, col. 1, para. 2).

Claim 1 has been amended to recite “an image processing system having image data processing means of automatic adaptation of 3-D Mesh Model to image features, for Model-based image segmentation, comprising means of dynamic adaptation of Model resolution to image features including means of locally setting higher resolution when reliable image features are found and means of setting lower resolution in an opposite case, wherein reliability of an image feature is based on a feature distance and noise; and comprising viewing means for visualizing images.”

The Examiner asserts that points of high curvature inherently have increased information content in the form of more high frequency content and are consequently more reliable indications of shape than points of low curvature. (See 7/11/08 Office Action, p. 5). Furthermore, the Examiner asserts that, under claim 1, any feature can be qualified as a “reliable image feature,” and therefore all high curvature regions qualify as reliable image features. (See 1/21/09 Office Action, p. 2). Applicants submit that having points of high curvature does not necessarily mean that there are more reliable image features. For example, a noisy image region, and hence being an unreliable image feature, may have many points of high curvature. This is because a determination of surface curvature involves taking partial second order derivatives of the surface, and the computation of the partial second order derivatives is very sensitive to noise. A high frequency noise in the image may result in a very high curvature value because the noise is found in the high frequency content. Since a noisy image having high curvature values is not a reliable image feature, therefore, an area having points of high curvature value does not necessarily imply that it is a reliable image feature. Thus, for the present example of an unreliable noisy image feature, the teaching of Delingette would require setting a higher resolution. In contrast, claim 1 recites “setting higher resolution when reliable image features are

found and *means of setting lower resolution in an opposite case.*” That is, setting a lower resolution when reliable image features are not found. Therefore, Delingette fails to disclose the above stated limitation.

Furthermore, Applicants respectfully submit that Bernardini does not cure the above-mentioned defects in Delingette. Bernardini discloses a method and apparatus for finding a triangle mesh that interpolates a set of points obtained from a scanner. (See Bernardini, col. 3, lines 47-49). Multiple scans of an object are aligned into a single coordinate frame, their points forming an unorganized point cloud. (See Bernardini, col. 6, lines 5-7). The disclosed ball-pivoting algorithm then connects these points as a series of triangles by “rolling” a ball of a given radius between the points. (See Bernardini, Abstract). The algorithm continues until all the points in the cloud have been considered. (See Bernardini, Abstract). The algorithm generates an output mesh that is a manifold subset of an alpha-shape of the point cloud. (See Bernardini, col. 5, lines 33-35). The alpha shapes are an effective tool for computing the “shape” of the point cloud. (See Bernardini, col. 7, lines 18-19). The final output is a representation of the geometry of the scanned object in a computer model. (See Bernardini, col. 1, lines 30-31).

Bernardini considers sources of error in its measurement system. (See Bernardini, col. 1, lines 41-53, and col. 7, line 24 through col. 9, line 11). There are two sources of error: error in registration, and error along the sensor line of sight. (See Bernardini, col. 1, lines 49-51). Typical problems are missing points, non-uniform density, imperfectly aligned overlapping range scans, scanner line of sight error, and outliers. (See Bernardini, col. 8, lines 12-20). These are the problems that Bernardini considers “noise.” Bernardini has ways of dealing with each problem. First, Bernardini discusses the holes created by “missing points.” The points can be missing for several different reasons, including non-uniform density of the scanned point cloud, whether parts of the surface were not scanned, or when the points are missing because of some line of sight error. (See Bernardini, col. 8, lines 5-11 and 26-57). Due to these “noise” errors, certain parts of Bernardini’s surface will be unreliable. In this situation, Bernardini teaches a method of filling these holes in, *increasing the resolution* in these areas, rather than decreasing the resolution. (See Bernardini, col. 8, lines 44-57). For instance, it describes a process of filling the holes in by applying the ball-rolling algorithm multiple times, increasing the ball radius each

time. (See Bernardini, col. 8, lines 44-48). Second, Bernardini discusses the errors caused by improperly aligned overlapping scans. (See Bernardini, col. 8, line 58 through col. 9, line 6). The noisy sample forms two layers, distant enough to allow the ball to walk on both layers. (See Bernardini, col. 8, lines 60-62). When Bernardini encounters this phenomenon, it *increases the resolution* of that noisy area by allowing the formation of undesired small connected components lying close to the main surface. (See Bernardini, col. 8, lines 62-64). Although the seed triangle selection process tries to avoid creating a large number of these small components, post-processing is required to remove them and smooth the surface. (See Bernardini, col. 8, line 64 through col. 9, line 6). Finally, Bernardini discusses the problem of outliers. (See Bernardini, col. 8, lines 15-20). Bernardini suggests that outliers should be removed by the scanning device in pre-processing, thus simply *ignoring* this type of noise.

Thus, for these examples of unreliably noisy image features, the teachings of Bernardini would require either using a higher resolution, or simply ignoring the problem. In contrast, as described above, claim 1 recites “setting higher resolution when reliable image features are found and *means of setting lower resolution in an opposite case.*” That is, setting a lower resolution when reliable image features are not found. Furthermore, Vannah does not cure the above described deficiencies of Delingette and Bernardini.

Accordingly, Applicants respectfully submit that neither Delingette, Bernardini nor Vannah, either alone or in combination, teach or suggest a “means of dynamic adaptation of the Model resolution to image features including means of locally setting higher resolution when reliable image features are found and means of setting lower resolution in the opposite case, wherein a reliability of an image feature is based on a feature distance and noise” as recited in claim 1. Because claims 2-14 depend from, and therefore include all the limitations of claim 1, it is respectfully submitted that these claims are also allowable for at least the same reasons given above with respect to claim 1.

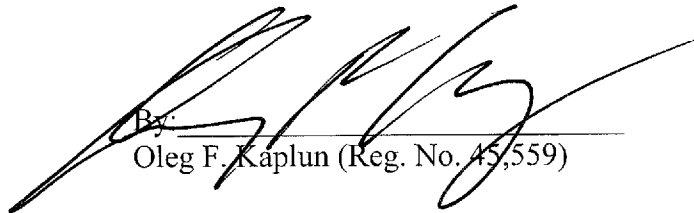
Claim 15 has been amended to contain essentially the same language as claim 1. Thus, Applicants respectfully submit that claim 15 is allowable for at least the same reasons given above with respect to claim 1.

**CONCLUSION**

In light of the foregoing, Applicants respectfully submit that all of the now pending claims are in condition for allowance. All issues raised by the Examiner having been addressed, an early and favorable action on the merits is earnestly solicited.

Respectfully submitted,

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